

Shifts in Herd Mentality of Investors in Uncertain Market Conditions: New Evidence in the Context of a Frontier Stock Market

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Abstract: This paper examines the herding phenomenon in the context of a frontier stock market, the Colombo Stock Exchange of Sri Lanka, employing the cross-sectional absolute deviation methodology to daily frequencies of data for the period from April, 2000 to September, 2016. The results show significant changes in magnitude and pattern of herding over different episodes of the market. The herd behavior is strongly presence irrespective of the direction of the market movement in the 2000-2008 period, during which investments in the stock market is affected by the country's political instability resulting from the civil war. The evidence also shows herd behavior during the period of market bubble whereas negative herding in the market crash period. However, it becomes less likely to occur during the period after the market crash. The lower tendency to herd during the post-market crash period supports the Adaptive Market Hypothesis, implying that investors are likely to realize the irrationality of herding and learn to be more rational as a consequence of significant losses experienced during the period of the market crash. Accordingly, these findings suggest that period-specific characteristics of the market and the associated psychological effects to investors such as overconfidence and panics would cause changes to their beliefs and behavior, the experiences of which would subsequently produce learning effect to minimize their irrationality in decision making.

Keywords: *Time-varying herd behavior; negative herding; adaptive market hypothesis; investor learning; quantile regression.*

1. Introduction

The herding is one's tendency to behave by imitating the actions of others while neglecting his/her private information and beliefs. It can be concerned as a rational or an irrational one depending on whether it occurs intentionally or unintentionally¹. However, many studies claim herding as an intentional act, since market characteristics such as uncertainties, asymmetric flow of information and structural limitations (for example, lower transparency of informational environment, illiquidity and low number of stocks actively traded) would affect to investors' psychological state, encouraging them to imitate others' behaviors when trading their financial assets. For instance, when the market is uncertain and information becomes less available, investors may fear of using their own judgments, thus they would tend to follow others in trading stocks. Such behavior is regarded as irrational due to its unfavorable consequences to a financial market such as turmoil, crashes, increased volatility, and information cascades², which decrease its efficiency and hinder its development.

The herd behavior is also considered to be a time-varying phenomenon (that is, nature and magnitude of this irrational tendency would change over time) since market environment is subject to continuous changes, for example, with rise or decline in market uncertainties, and developments, for example, with policy initiatives by regulators to control market's structural limitations. Apart from the time-varying nature of herding, a different view of this herding phenomenon can be hypothesized based on the Adaptive Market Hypothesis (AMH), a new framework on market behavior introduced by Lo (2004, 2005, 2012). The AMH implies investors are not completely rational or irrational, but are intelligent and forward-looking so that they are

¹For detailed discussion on intentional and unintentional herding, see Dang and Lin (2016); Galariotis, Rong, and Spyrou (2015); Gavrilidis, Kallinterakis, and Ferreira (2013); Guney, Kallinterakis, and Komba (2017); Holmes, Kallinterakis, and Ferreira (2013); Tan, Chiang, Mason, and Nelling (2008).

²Since herd behavior results in suppressing market participants' private information and beliefs, market prices are determined through a limited amount of information (Banerjee, 1992; Bikhchandani, Hirshleifer, & Welch, 1992).

capable of learning their irrational behaviors for adapting to dynamic market conditions. Considering the insights of the AMH and based on the learning literature³, it could be expected that investors would realize the irrationality of herding and tend to control such behaviors when they get experience over time in stock trading⁴. Accordingly, while the herding is predicted to be a time-varying behavior, it would characterize a declining trend over time with the investor's mistake-learning process. Accordingly, the objective of this study is to examine whether the investors' herd behavior change over time, depending on the context in which trading takes place, and tend to minimize it with their trading experiences.

This study examines the herd behavior in a frontier stock market; the Colombo Stock Exchange (CSE)⁵ of Sri Lanka, which is worthwhile in the following respect. First, as discussed above, the herding is predicted to be more prominent in a frontier market due to its structural limitations at the pre-emerging stage. Second, over the last two decades, the CSE passed by different market episodes such as uncertain market period resulting from unstable political conditions of the country, rising the market to a speculative bubble and market crash (see Figure 1), during which investors would have experienced significant psychological shocks and changed their irrational behaviors so that, consistent with the AMH and the learning theories, herding would have disappeared or, at least, declined over these time periods. Thus, the CSE appears to be an appropriate setting for the examination of this shift in herd mentality of investors, which is a novel attempt for contributing towards the time-variation of the herd behavior, hypothesized in the literature. Third, there is a very limited volume of empirical studies currently available in the context of frontier stock markets, with some mix evidence on the occurrence of such behavior. Finally, the previous studies have mostly employed the ordinary least square (OLS) regression procedure, however revealed no information on whether its underlying error distribution assumptions are fulfilled. Since inaccurate estimates may result if those assumptions are not fulfilled, the validity of the evidence reported in the current literature appears to be doubtful. Therefore, the literature on herd behavior in the context of frontier markets is limited not only in terms of the quantity of studies, but also in the form of the quality of reported findings.

Accordingly, while attempting to fill these gaps in the literature, this study intends to contribute towards the time-variation of herd behavior in the context of frontier market as follows. Unlike the previous studies, it does not limit analysis to the total sample period. The analysis is also extended to the two eight-year and four four-year sub-periods as a robustness check of the results reported and to study the time-varying herding phenomenon. Further, the analysis is conducted separating the 2008-2016 high volatile period into market bubble, crash, and post-crash periods in order to examining whether investors' herding attitudes tend to shift away over these episodes of the CSE. In addition to applying customary used OLS approach, this study employs the quantile regression (QR) procedure which provides deeper analysis of herding and robust evidence even when the parametric assumptions of error distribution are not fulfilled, so that validity and reliability of the results will be improved. The remainder of the paper is organized as follow. Section 2 provides a review of literature mainly focusing on the evidence relating to frontier stock markets. Section 3 and 4 explain respectively data and methodology employed in detecting the herding behavior. The evidence on the herd behavior for the total sample period and during different episodes of the market and its time-varying nature are discussed in section 5. Section 6 concludes the paper.

³Such as those concern on cognitive aspect (for example, transformative learning theory) and behavioral aspect (for example, reinforcement learning theory) of learning, which suggest that experiencing a shock to an individual's psyche such as "disorienting dilemma" is the starting point for learning to occur within the individual. Disorienting dilemma is a psychological discrepancy between what an individual expected to happen and what is actually experienced.

⁴ There is a plenty of evidence for the support of the hypothesis that trading experience could reduce irrational behaviors and thereby, improve investment performance. See, for example, Barber and Odean (2011); Bradbury, Hens, and Zeisberger (2014); Dhar and Zhu (2006); Feng and Seasholes (2005); Gervais and Odean (2001); Itzkowitz and Itzkowitz (2017); List (2011); Nicolosi, Peng, and Zhu (2009); Seru, Shumway, and Stoffman (2009).

⁵Refer to the Morgan Stanley Capital International (MSCI) frontier market index which recognizes the CSE as a frontier market.

2. Literature Review

The behavioral finance literature provides an ample of evidence on the existence of herding in the context of both developed and emerging equity markets through variety of studies, focusing mainly, among other, the herd behavior among different groups⁶, different nature of herding⁷, and its determinants⁸. The literature has also recognized this behavioral pattern as a time-varying phenomenon and its occurrence in different episodes of a stock market such as bubbles and crashes, and during specific economic events such as financial crises⁹. However, in spite of a plenty of evidence in the contexts of developed and emerging equity markets, the evidence relating to frontier stock markets is currently limited (Balcilar, Demirer, & Hammoudeh, 2014; Economou, Gavrilidis, Kallinterakis, & Yordanov, 2015; Guney et al., 2017).

The herding literature on frontier markets has limited in terms of both volume and consistency of results reported on the occurrence of such behavior. To this respect, Balcilar, Demirer, and Hammoudeh (2013) found herding in frontier stock markets of Middle East countries, namely Saudi Arabia, Dubai and Qatar, but not for Kuwait and Abu Dhabi. Similarly, the study conducted by Guney et al. (2017) revealed herd trading patterns in the markets of Botswana, BRVM¹⁰, Ghana, Kenya, Namibia, Nigeria, Tanzania and Zambia. In addition, Vo and Phan (2016) showed herding patterns in Vietnam stock market. However, studies of Ahsan and Sarkar (2013), applying a methodology similar to those of other studies¹¹, found no evidence of herding on the Bangladesh stock market. When the determinants of herding in frontier markets are concerned, Vo and Phan (2016) revealed significant differences of herd behavior between up-market days and down-market days, and pre-crisis and post-crisis periods. However, Guney et al. (2017) found no such strong evidence on the herding asymmetries between up and down market movements. The study conducted by Ahsan and Sarkar (2013) also revealed no evidence of herding in both of these market movements. Further, Balcilar et al. (2013) and Guney et al. (2017) find asymmetries with respect to high and low volatility days, suggesting the market volatility as a determinant of herd evolution in frontier markets.

Similar to the other frontier stock markets, the empirical studies in the context of the CSE are currently limited and provide in conclusive evidence on the occurrence of herding behavior. According to my knowledge, Sewwandi (2016) was the first to examine whether the investors of the CSE exhibit herd behavior in stock trading. It estimated the herd behavior for the aggregate market and separately for raising and falling market days, following the approach proposed by Chang et al (2000) with OLS regression. The results show no evidence of herd formation over the period from 2001 to 2015, indicating that investors behave rationally in trading stocks. Subsequently, Xiaofang and Shantha (2017) investigated on this phenomenon, employing both OLS and QR procedures for the non-financial firms listed during the period from 2007 to 2016. They found presence of herd behavior based on the QR procedure, however no evidence under the OLS procedure. Taken together, due to the limitations in the current literature, in terms of its volume and consistency of results, it is inconclusive as to whether the investors of the CSE tend to herd, or shift away from such irrational behavior in stock trading.

Data: Sample period of the study spans from 1st April 2000 to 30th September 2016 and covers different episodes of the CSE (See figure 1). The first half of the sample period, 2000-2008 characterizes a period of

⁶For example, herding by institutional investors, herding on analyst's recommendations, and market-wide herding (that is, market participants' collective behavior towards a consensus).

⁷For example, intentional herding, unintentional herding (spurious herding), herding on macro-economic fundamentals, and cross-country effect on herd behavior.

⁸For example, size (small stock vs. large stocks), industry, market performance (up-market days vs. down-market days), volatility, market sentiments, and trading volume. The previous studies also identified herding asymmetry with respect to these determinants.

⁹See, for example, Bekiros, Jlassi, Lucey, Naoui, and Uddin (2017); Clements, Hurn, and Shi (2017); Klein (2013); Zhou and Anderson (2013).

¹⁰BRVM is abbreviated for "Bourse Régionale des Valeurs Mobilières", a regional stock exchange of West Africa.

¹¹ All the studies discussed here have examined herding using the cross-sectional absolute deviation (CSAD) model of Chang, Cheng, and Khorana (2000).

unstable political conditions of the country due to civil war, which could impact on trading and investment on the CSE. Since the end of the civil war in May 2009, the market experienced a rapid growth, rising to a speculative bubble which burst over the period from March, 2011 to July, 2012. It is expected that such a longer period with different episodes of the CSE assists in examining time-varying herding attitudes of investors with these period specific characteristics of the market. All the common stocks listed on the CSE during the sample period are considered, extracting the required stock prices from the Data Library (CD ROM) published by the CSE. As herd behavior is more evident with daily frequencies of data, the analysis is based on the same over the sample period which consist a total of 3955 daily observations.

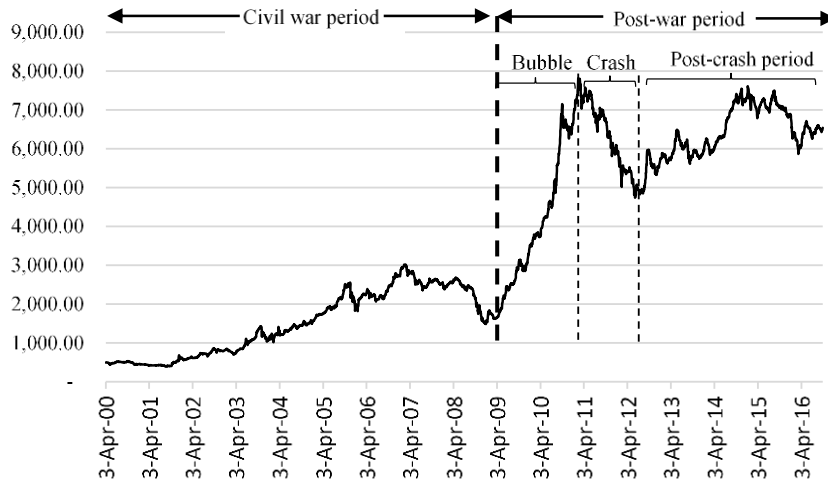


Figure 1: Movement of Stock Market Index of CSE

3. Methodology

The CSAD Model: This study employs the cross-sectional absolute deviation (CSAD) model of Chang et al. (2000), as shown in equation (1).

$$CSAD_t = \alpha + \gamma_1 |R_{mt}| + \gamma_2 R_{mt}^2 + \varepsilon_t \dots \dots \dots (1)$$

where R_{mt} is the equally-weighted average return of all stocks on day t , and $|R_{mt}|$ is the absolute value of R_{mt} , and $CSAD_t$ is the equally weighted cross-sectional absolute deviation of stock return on day t , determined as in equation (2).

$$CSAD_t = (1/N) \sum_{i=1}^N |R_{it} - R_{mt}| \dots \dots \dots (2)$$

where R_{it} is return of stock i on day t , calculated as the first logarithmic difference of daily closing prices and N is the number of firms in the market portfolio on day t .

The CSAD model is, among other, the most widely applied empirical specification for detecting market-wide herding¹². Since investors are expected to trade stocks based on their diverse information and beliefs, as the capital assets pricing model (CAPM) predicts, the CSAD model assumes stock returns are linear and

¹²Christie and Huang (1995) was first to test market-wide herding, examining cross-sectional standard deviation (CSSD) of security returns at the extreme lower and upper tails of the return distribution. This method suffers drawbacks such as biased CSSD in the presence of outliers (Economou, Kostakis, & Philippas, 2011), ignoring the possibility of non-linear return dynamics associated with herding (Focardi, Cincotti, & Marchesi, 2002; Lux, 1995), difficulties in defining the extreme returns (Chiang, Li, & Tan, 2010), and disregarding the possibility of herding during stable time periods (Bekiros et al., 2017). Since CSAD model overcomes these drawbacks, it has been widely used in herding studies. However, both models predict herding when stock returns converge to overall market return.

increasing function of portfolio of market returns. This assumption implies a positive relationship between CSAD of returns and absolute market return (a significant positive value for γ_1 and insignificant γ_2 in equation (1)). However, in case of herding, investors disregard their private information and beliefs, and follow market consensus (market-wide price movements). Then, stock returns tend to cluster around the market average, decreasing the CSAD of returns so that the positive relationship between CSAD of returns and market return turns to be negative and non-linear, which is captured through γ_2 , the coefficient of R_{mt}^2 term in equation (1). Accordingly, the coefficient γ_2 would be significantly negative in the presence of herding behavior. On the other hand, as reported by number of previous studies¹³, it is possible to occur “negative herding” (also called as “reverse herding”) where investors tend to resort to a particular dominant view, ignoring information conveyed by market-wide price movements. As noted by Gębka and Wohar (2013), the negative herding behavior may be caused by localized herding (correlated actions of group of investors who irrationally move into/(out of) a position of a particular subset of stocks, resulting excessive increase/(decrease) in stock prices), irrational fears in periods of uncertain market conditions (which motivate investors to be more risk-averse so that they rebalance their portfolios to more secure positions by selling risky and buying less risky stocks), or overconfidence of investors. These result in trading a subset of assets excessive and exaggerate way, increasing the price dispersions above the level predicted by the CAPM. Accordingly, the negative herding is evident from a significant positive value of γ_2 in equation (1).

Test of Herding Conditional on Market Performance: In addition to the test of herding behavior in relation to the aggregate market as in equation (1), the empirical tests are carried out using the CSAD model to detect herding conditional on the direction of market movement (that is, herd behavior during up-market days vs. down-market days), as depicted in equation (3).

$$CSAD_t = \alpha + \gamma_1 D_t^{up} |R_{mt}| + \gamma_2 D_t^{up} R_{mt}^2 + \gamma_3 (1 - D_t^{up}) |R_{mt}| + \gamma_4 (1 - D_t^{up}) R_{mt}^2 + \varepsilon_t \dots \dots (3)$$

where, D_t^{up} is the dummy variable representing the value of unity for up-market days (days with $R_{mt} > 0$) and zero for down-market days (days with $R_{mt} < 0$). The Wald test is employed to test whether the herding during the up-market days is asymmetry from that in the down-market days (In other words, whether γ_2 is significantly different from γ_4).

Ordinary least squares vs. Quantile regressions: The coefficients of the models shown in equation (1) and (3) are estimated using the OLS regression method, where the conditional mean of the dependent variable, $CSAD_t$, is regressed with respect to the set of independent variables in each model. However, the OLS suffers from serious statistical weaknesses such as sensitiveness of estimates to outliers, inappropriate to account for non-linearity, and inaccurate results when error distributional assumptions are not fulfilled¹⁴. Therefore, in order to improve the reliability of the results, the models are also estimated applying a more robust method, the QR procedure¹⁵. Since the QR estimates are semi-parametric, they are less sensitive to outliers in data and do not require fulfilling the parametric assumptions of the error distribution such as normality and Heteroskedasticity¹⁶. Thus, when compared with the OLS, the QR is a more powerful method in modeling the relationship between the CSAD of returns and portfolio of market returns for detecting the herd behavior. Further, with the application to herding analysis, the QR provides complete description on how herding estimates vary over the entire distribution of the CSAD, thus reveals the evidence on herding under extreme market conditions (extreme upper and lower quantile intervals). The QR models for estimating herding on the aggregate market and separately for up and down market days are given in equation (4) and (5) respectively.

$$Q_\tau(\tau|CSAD_t) = \theta_\tau + \gamma_{1,\tau} |R_{mt}| + \gamma_{2,\tau} R_{mt}^2 \dots \dots \dots (4)$$

¹³See, for example, Bekiros et al. (2017); Chiang and Zheng (2010); Economou et al. (2011); Gębka and Wohar (2013); Klein (2013) for the discussion on the negative herding.

¹⁴ See Barnes and Hughes (2002); Wilcox (2010); Zhou and Anderson (2013).

¹⁵ The QR, introduced by Koenker and Bassett (1978), has been profoundly used with econometric analysis and financial research over the past decades (Allen et al., 2012). Despite this, a very limited number of empirical studies applied this method to examine herding behavior (Bekiros et al., 2017).

¹⁶ See Alexander (2008); Allen et al. (2012); Barnes and Hughes (2002); Cade and Noon (2003); Xiao (2012).

$$Q_{\tau}(\tau|CSAD_t) = \theta_{\tau} + \gamma_{1,\tau}D_t^{up}|R_{mt}| + \gamma_{2,\tau}D_t^{up}R_{mt}^2 + \gamma_{3,\tau}(1 - D_t^{up})|R_{mt}| + \gamma_{4,\tau}(1 - D_t^{up})R_{mt}^2 \dots (5)$$

where τ represents for quantiles. For any $\tau \in \{0, \dots, 1\}$, the coefficients of R_{mt}^2 capture the increase or decrease in CSAD of return beyond its rational level predicted by the CAPM. The coefficients are estimated minimizing the weighted sum of absolute errors, where weights directly depend on quantiles¹⁷. For computing the confidence intervals of the regression quantiles, the bootstrap technique¹⁸ is employed with xy-pair design¹⁹ and 600 replications²⁰.

Test of Time-Varying Herd Behavior: In order to examine changes in herd behavior over time, the total sample period is split into two eight-year sub-periods and four four-year sub-periods. The first eight-year period, 2000-2008 characterizes a period of political instability of the country due to civil war. The second eight-year period, 2008-2016 which is more volatile than first eight-year period (see figure 1) is further investigated, separating into three sub-periods, namely market bubble (February 2009 to February 2011), market crash (March 2011 to July 2012) and post-crash (August 2012 to September 2016) periods. All the tests, as given in equations (1), (3), (4) and (5) above are repeated for those sub-sample periods as a robustness check of the results and to test time-varying nature of herd behavior.

Table 1 provides descriptive statistics for $CSAD_t$ and R_{mt} over the total sample period and different sub-periods considered for the analysis. Except for the market crash period, the mean value of R_{mt} is positive during the sample period, showing positive market performance. Further, the magnitude of the volatility (as reflected by the standard deviation) of $CSAD_t$ is consistently lower than that of R_{mt} , indicating tendency of stock returns to cluster around the market return. Interestingly, the standard deviations of both R_{mt} and $CSAD_t$ are lower during the high-volatile period, 2008-2016 than those of 2000-2008 period. The Augmented Dickey-Fuller (ADF) test statistics of both variables are statistically significant, rejecting the null hypothesis of the unit root, thus the variable series are stationary. R_{mt} and $CSAD_t$ series seem to deviate from normal distribution as their Jarque-Bera statistics are statistically significant. The distribution of $CSAD_t$ is also skewed to the right as reflected by higher positive skewness statistics. Thus, the QR results are important to discuss how herd tendency varies along the tail of the distribution of $CSAD_t$. The non-normality of $CSAD_t$ further highlights the importance of the QR analysis to provide robust evidence and to check the validity of the OLS results reported in this study.

Table 1: Descriptive statistics

		Mean	Standard Deviation	Skewness	Jarque-Bera statistic	ADF statistic
Panel A: Total Sample;						
	$CSAD_t$	1.068	0.405	2.148	11038.11***	-11.736***
	R_{mt}	0.059	0.740	0.269	44121.50***	-43.813***
Panel B: 8-year sub-periods;						
2000 - 2008	$CSAD_t$	1.176	0.487	1.847	2612.72***	-10.984***
	R_{mt}	0.078	0.872	0.185	18879.09***	-31.910***
2008 - 2016	$CSAD_t$	0.968	0.272	1.324	1538.64***	-7.469***
	R_{mt}	0.041	0.590	0.363	5120.70***	-22.101***

¹⁷ The quantile regression estimates are obtained by using views® (Version 8, 2013).

¹⁸ Refer Chen and Wei (2005); Kocherginsky, He, and Mu (2005); Koenker (1994); Koenker and Hallock (2000) for different methods of computing confidence intervals under the QR and their comparisons. According to their results, differences between these methods are slight, and the bootstrap technique appears to be suitable for a study with a small sample (<5,000) and small number of covariates (<20).

¹⁹ Based on the simulation results reported by Buchinsky (1995) and Machado and Silva (2013), xy-pair bootstrap estimator provides valid standard errors, compared to other bootstrap estimators.

²⁰ Consistent with the guidelines provided by Andrews and Buchinsky (2000) and Koenker and Hallock (2000).

Table 1: Descriptive statistics (*continued*)

		Mean	Standard Deviation	Skewness	Jarque-Bera statistic	ADF statistic
Panel C: 4-year sub-periods;						
2000 - 2004	$CSAD_t$	1.128	0.449	1.677	1488.37***	-9.232***
	R_{mt}	0.082	0.920	0.915	15282.93***	-22.324***
2004 - 2008	$CSAD_t$	1.223	0.517	1.912	1089.71***	-7.590***
	R_{mt}	0.074	0.821	-0.843	2854.23***	-29.420***
2008 - 2012	$CSAD_t$	1.024	0.288	1.505	1088.44***	-6.743***
	R_{mt}	0.063	0.724	0.294	1559.03***	-25.717***
2012-2016	$CSAD_t$	0.918	0.248	1.023	241.88***	-7.733***
	R_{mt}	0.022	0.439	0.268	323.08***	-12.511***
Panel D: Volatile period 2008-2016;						
Bubble period	$CSAD_t$	1.008	0.248	1.096	189.20***	-5.011***
	R_{mt}	0.161	0.571	-0.168	206.25***	-18.616***
Crash period	$CSAD_t$	1.080	0.289	1.842	824.79***	-6.298***
	R_{mt}	-0.059	0.766	0.678	624.59***	-15.496***
Post-crash period	$CSAD_t$	0.899	0.237	1.065	260.95***	-8.057***
	R_{mt}	0.028	0.412	0.201	195.66***	-12.075***

This table reports summary statistics, tests of normality and test of non-stationary of the cross-sectional absolute deviation of returns ($CSAD_t$) and the market return (R_{mt}) series over the sample period from 3/4/2000 to 30/9/2016. All sub-periods in panel B and C start from 1st April and end 31st March of the given year, except the last sub-period which ends 30th September 2016. Panel D shows further analysis of 2008-2016 period, classifying into periods of market bubble (February, 2009 to February, 2011), market crash (March, 2011 to July, 2012) and post-crash (August, 2012 to September, 2016). ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

4. Results and Discussion

The coefficient - γ_2 in equation (1) and (4) represents respectively the OLS and the QR estimates of herding at the aggregate market, while coefficients - γ_2 and γ_4 in equation (3) and (5) reflect respectively the OLS and the QR estimates of herding in days of up-market and down-market movements. These estimates, where a significant negative/ (positive) value indicates herd behavior/ (negative herding), are presented separately for the total sample period, eight-year sub-periods, four-year sub-periods, and periods of market bubble, crash and post-crash respectively in Panel A, B, C and D of Table 2, 3, 4 and 5. The empirical results are discussed in the following manner. First, the results of the total sample period are discussed in order to compare them with those of the previous studies on the CSE. After that, the analysis is performed across different sub-periods to examine whether herding is time-varying phenomenon. The coefficients of the absolute market return, γ_1 in equation (1) and (4) and γ_1 and γ_3 in equation (3) and (5), are significantly positive in both total sample period and sub-sample periods, supporting the hypothesis on the positive relationship between the CSAD of returns and absolute market returns.

Herd Behavior over the Entire Sample Period: Both the OLS and the QR herding estimates for the total sample period (2000-2016) reveal a tendency to herd at both the aggregate market and up and down market days, as reflected by significantly negative values for γ_2 in panel A of Table 2 and 3 and for γ_2 and γ_4 in panel A of Table 4 and 5. These findings are in contrast to the study undertaken by Sewwandi (2016), which, applying the OLS procedure, found no evidence of herd behavior at the aggregate market and up and down market days during the 2001-2015 period. On the other hand, the evidence reveals no asymmetry of herding between up and down market days of the total sample period, since both the OLS and the QR analyses find an insignificant difference between γ_2 and γ_4 (as shown by insignificant F statistic), which suggests, consistent with Klein (2013), Bekiros et al. (2017) and Xiaofang and Shantha (2017), that the herding is unconditional

occurrence, therefore arising independently from the direction of the market movement. Further, the QR estimates indicate that herding appears to be stronger during extreme market movements, as reflected by increases of γ_2 and γ_4 from median quantile (0.50) to highest (0.95) and lowest (0.05) quantile intervals.

Time-Variation of Herd Behavior: The empirical results are compared across different episodes of the CSE such as periods of uncertain political conditions, market bubble and crash, and post-crash to examine whether herding is a time-varying phenomenon and shifts in investors' herding attitudes occur with these period specific characteristics of the market, as follows.

Herd behavior during the period of political uncertainty: The first half of the sample period, 2000-2008 characterizes a period of unstable political conditions of the country due to civil war, which would cause uncertainties in the mind of investors when investing and trading of stocks. Thus, the analysis of the results relating to this time period reveals evidence as to whether market uncertainties would trigger investors to exhibit a strong tendency to herd²¹. With respect to both the OLS and the QR results of the aggregate market, as reported in panel B of Table 2 and 3 respectively, γ_2 is significantly negative for the 2000-2008 period, revealing the presence of herding attitudes among investors. In addition, both the OLS and the QR estimates of γ_2 and γ_4 , shown in panel B of Table 4 and 5 respectively, find herding in both directions of the market movement.

These results are also consistently evident for the two four-year sub-periods from 2000 to 2008, as given in panel C of Table 2 and 4. Notably, the QR results further highlight an increase of γ_2 and γ_4 from median quantile (0.50) to the extreme upper (0.95) and the extreme lower (0.05) quantile intervals, indicating stronger tendency to herd during the extreme market conditions. With respect to the asymmetry of herd behavior, the OLS evidence reveals a stronger tendency to herd towards down market direction since Table 4 shows greater γ_4 than γ_2 with significant F statistics for the sub-periods of 2000-2008 (panel B) and 2000-2004 (panel C). However, the QR evidence which is more robust than that of the OLS, provides no support for such herd asymmetry. Accordingly, the evidence infers that the direction of market movement has not been a determinant for herd evolution. Therefore, when the results are taken together, it appears that market uncertainties would trigger investors to herd in both up and down market movement days, disregarding their private information and belief.

Herd behavior during the market bubble and market crash periods: It is interesting to compare the herding estimates obtained separately for the periods of market bubble and crash, as provided in panel D of Table 2, 3, 4 and 5. When the OLS results for the aggregate market, as shown in panel D of Table 2 are concerned, the coefficient γ_2 is significantly negative during the period of market bubble whereas it is significantly positive in the subsequent crash period. Since a significant positive value reveals negative herding patterns, the directionality of the herd behavior seems to have changed during the period of the market crash. The evidence obtained using the QR approach, as shown in panel D of Table 3, also suggests herd behavior during the bubble period (as coefficient γ_2 is significantly negative at lower and middle quantiles) and negative herding during the market crash period (as reflected by significantly positive γ_2 at lower quantiles).

In addition, the OLS results (panel D of Table 4) and the QR results (panel D of Table 5) obtained separately for up and down market days show this change in herding patterns, where herd behavior towards up-market direction in the bubble period shifts to negative herding in down-market direction during the market crash period. Accordingly, investors appeared to disregard fundamentals and follow considerably market-wide price movements such as positive price signals emitted in the market from the end of civil war, which resulted to a speculative bubble in the market (Bekiros et al., 2017). Then, investors who realized significant gains in the market bubble period may become overconfident and those who were fear of the uncertainty associated with the market bubble may become risk averse and rebalance their portfolios to more secure

²¹The analysis has also been performed by separating the sample period into pre and post war periods, using the date on which the end of the civil war officially declared in the parliament - 19th May 2009 as the cut-off point. The results of this analysis have not been reported here since they provide no contradictory evidence to those of the eight-year sub-periods reported in the paper.

positions, leading to negative herding which ends up in crash of the market (Gębka, & Wohar, 2013). Therefore, as evidence suggests, herd behavior and its shift to negative herding appear to cause a higher volatility in the market with a speculative bubble and its subsequent crash.

Herd behavior during the post-crash period: Another interesting result here is that, consistent with the findings of Zhou and Anderson (2013) and Gębka and Wohar (2013), the magnitude of herding appears to reduce in the period after market crash, revealing a tendency to decrease investors' herding attitudes in response to unfavorable market experiences. As shown in panel D of Table 2, the absolute value of the coefficient of γ_2 which is 0.104 and highly significant at 1% level during the period of bubble, reduces to 0.079 and 10% significance level in the post-crash period. Panel D of Table 4 also demonstrates this decreasing tendency of the magnitude of herding, where the coefficient of γ_2 in absolute terms during the bubble period is 0.127 and significant at 1% level whereas same in the post-crash period is 0.089 and significance at 10% level.

A similar behavior is revealed from the QR results presented in panel D of Table 3 and 5. The herd behavior being evident from lower to upper quantiles during the bubble period appears to limit to 0.05th quantile (Panel D of Table 3) and 0.75th quantile (Panel D of Table 5) in the period after the market crash. Supporting the prediction of the AMH and the learning theories, the lower tendency to herd during the post-crash period may be attributed to the learning effect resulting from significant experiences gained by investors during the periods of market bubble and crash. This implies that investors may have learnt the irrationality of herding and changed to a more rational trading behavior with significant losses and the associated psychological shocks occurred during the market crash period.

Table 2: Herding estimations for the aggregate market based on the OLS regression

	α	γ_1	γ_2	Adjusted R^2
Panel A: Total Sample	0.800 (64.470)***	0.599 (16.881)***	-0.038 (-4.157)***	0.454
Panel B: 8-year sub-periods;				
2000 – 2008	0.825 (43.558)***	0.681 (13.731)***	-0.049 (-3.986)***	0.484
2008 – 2016	0.806 (66.304)***	0.421 (13.431)***	-0.018 (-1.232)	0.370
Panel C: 4-year sub-periods;				
2000 – 2004	0.795 (36.453)***	0.623 (15.103)***	-0.035 (-5.266)***	0.587
2004 – 2008	0.819 (32.315)***	0.856 (10.891)***	-0.108 (-7.067)***	0.437
2008 – 2012	0.869 (48.036)***	0.304 (7.985)***	0.010 (0.652)	0.369
2012 – 2016	0.753 (50.798)***	0.544 (10.172)***	-0.043 (-1.243)	0.356
Panel D: Analysis of 2008-2016 sub-period;				
Bubble period	0.846 (35.361)***	0.447 (6.654)***	-0.104 (-3.037)***	0.200
Crash period	0.945 (41.341)***	0.205 (4.320)***	0.048 (3.900)***	0.426
Post-crash Period	0.739 (50.053)***	0.567 (9.932)***	-0.079 (-1.715)*	0.316

This table presents estimates of equation (1). All sub-periods in panel B and C start from 1st April and end 31st March of the given year, except the last sub-period which ends 30th September 2016. Panel D shows further analysis of 2008-2016 period, classifying into periods of market bubble (February, 2009 to February, 2011), market crash (March, 2011 to July, 2012) and post-crash (August, 2012 to September, 2016). The numbers in parentheses are *t*-statistics based on the Newey and West (1987) test for Heteroskedasticity and autocorrelation consistent standard errors. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

Table 3: Herding estimations for the aggregate market based on the QR (*continued*)

Quantile	θ_τ	γ_1	γ_2	Adj. R^2	θ_τ	γ_1	γ_2	Adj. R^2
Panel A: Total Sample					Panel C: 4-year sub-periods <i>cont'd...</i>			
					(ii) 2012-2016			
0.05	0.533 (50.747)***	0.440 (11.985)***	-0.046 (-2.215)**	0.191	0.523 (27.918)***	0.464 (4.914)***	-0.065 (-0.749)	0.175
0.25	0.666 (104.513)***	0.463 (21.834)***	-0.027 (-3.286)***	0.217	0.646 (59.643)***	0.420 (6.522)***	0.025 (0.498)	0.181
0.50	0.776 (82.348)***	0.539 (18.538)***	-0.027 (-2.535)**	0.240	0.716 (54.318)***	0.517 (9.093)***	-0.014 (-0.358)	0.207
0.75	0.912 (79.816)***	0.627 (18.948)***	-0.031 (-2.687)***	0.275	0.825 (50.268)***	0.674 (8.130)***	-0.091 (-1.888)*	0.213
0.95	1.109 (62.498)***	1.146 (13.443)***	-0.086 (-2.414)**	0.374	1.096 (29.402)***	0.677 (5.445)***	-0.124 (-1.529)	0.202
Panel B: 8-year sub-periods; (i) 2000 – 2008					Panel D: Analysis of 2008-2016 sub-period;			
					(i) Bubble period;			
0.05	0.500 (28.849)***	0.572 (10.809)***	-0.081 (-3.209)***	0.238	0.601 (27.732)***	0.287 (3.838)***	-0.035 (-0.837)	0.111
0.25	0.689 (58.823)***	0.517 (15.301)***	-0.038 (-3.359)***	0.241	0.714 (55.145)***	0.360 (8.136)***	-0.078 (-3.458)***	0.114
0.50	0.802 (63.903)***	0.601 (17.553)***	-0.037 (-2.872)***	0.272	0.816 (32.529)***	0.469 (6.054)***	-0.132 (-2.871)***	0.095
0.75	0.937 (47.362)***	0.736 (12.099)***	-0.043 (-2.281)**	0.309	0.958 (37.166)***	0.469 (5.053)***	-0.072 (-1.130)	0.107
0.95	1.153 (42.918)***	1.259 (12.248)***	-0.098 (-2.408)**	0.396	1.196 (18.924)***	0.551 (2.366)**	-0.141 (-0.761)	0.130
(ii) 2008 – 2016					(ii) Crash period;			
0.05	0.547 (59.501)***	0.400 (12.338)***	-0.069 (-3.370)***	0.169	0.696 (28.304)***	0.076 (1.637)	0.087 (4.635)***	0.129
0.25	0.670 (89.062)***	0.381 (9.593)***	-0.025 (-0.796)	0.176	0.834 (32.599)***	0.090 (1.477)	0.076 (2.933)***	0.138
0.50	0.762 (91.050)***	0.450 (14.274)***	-0.027 (-1.585)	0.195	0.935 (39.384)***	0.189 (3.085)***	0.048 1.609	0.171
0.75	0.903 (64.083)***	0.483 (10.328)***	-0.017 (-0.854)	0.204	1.069 (37.311)***	0.216 (2.307)**	0.048 1.333	0.219
0.95	1.152 (37.926)***	0.541 (6.247)***	-0.034 (-1.302)	0.244	1.207 (20.862)***	0.433 (2.750)***	-0.011 -0.215	0.364
Panel C: 4-year sub-periods; (i) 2008-2012					(iii) Post-crash Period			
0.05	0.585 (32.252)***	0.313 (5.688)***	-0.042 (-1.420)	0.141	0.506 (28.902)***	0.544 (6.253)***	-0.155 (-1.971)**	0.173
0.25	0.724 (59.077)***	0.242 (5.654)***	0.023 (0.844)	0.160	0.641 (48.882)***	0.419 (5.523)***	-0.002 (-0.023)	0.167
0.50	0.831 (60.091)***	0.332 (7.707)***	0.001 (0.031)	0.169	0.703 (60.550)***	0.542 (8.604)***	-0.052 (-0.875)	0.193
0.75	0.979 (52.583)***	0.358 (5.959)***	0.007 (0.348)	0.194	0.806 (43.939)***	0.679 (5.915)***	-0.089 (-1.069)	0.188
0.95	1.204 (28.063)***	0.485 (3.901)***	-0.023 (-0.708)	0.275	1.095 (27.236)***	0.652 (4.070)***	-0.143 (-1.114)	0.156

This table presents estimates of equation (4) at different quantile levels for the total sample period, eight-

Table 3: Herding estimations for the aggregate market based on the QR (*continued*)

Quantile	θ_τ	γ_1	γ_2	Adj. R^2	θ_τ	γ_1	γ_2	Adj. R^2
year sub-periods, four-year sub-periods, and analyzing 2008-2016 sub-period into market bubble (February 2009 to February 2011), market crash (March 2011 to July 2012) and post-crash (August 2012 to September 2016) periods. All sub-periods in panel B and C start from 1 st April and end 31 st March of the given year, except the last sub-period which ends 30 th September 2016. The results relating to the 2000-2004 and 2004-2008 sub-periods are not reported under panel C since their results are not significantly different from those reported under the 2000-2008 sub-period in panel B. The numbers in parentheses are t-statistics based on bootstrap standard errors. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.								

Table 4: Herding estimations conditional on market performance based on the OLS

	α	Up-market days		Down-market days			F statistic
		γ_1	γ_2	γ_3	γ_4		
Panel A: Total Sample	0.799 (66.993)***	0.642 (20.819)***	-0.037 (-5.527)***	0.554 (13.494)***	-0.041 (-4.934)***	0.462	0.220
Panel B: 8-year sub-periods;							
2000-2008	0.817 (46.420)***	0.720 (17.761)***	-0.045 (-6.289)***	0.676 (11.971)***	-0.066 (-5.839)***	0.494	3.630*
2008-2016	0.809 (65.935)***	0.492 (16.155)***	-0.037 (-3.050)***	0.313 (7.241)***	0.011 (0.450)	0.386	5.685**
Panel C: 4-year sub-periods;							
2000-2004	0.790 (35.796)***	0.658 (16.093)***	-0.034 (-8.045)***	0.614 (11.643)***	-0.048 (-5.399)***	0.594	3.101*
2004-2008	0.818 (33.004)***	0.896 (12.818)***	-0.110 (-7.117)***	0.791 (8.307)***	-0.097 (-5.114)***	0.440	0.610
2008-2012	0.873 (48.564)***	0.391 (10.356)***	-0.015 (-1.205)	0.162 (3.279)***	0.054 (2.507)**	0.395	12.957***
2012-2016	0.753 (51.249)***	0.595 (10.785)***	-0.054 (-1.540)	0.502 (7.778)***	-0.054 (-1.028)	0.361	0.000
Panel D: Analysis of 2008-2016 sub-period;							
	0.856 (35.527)***	0.533 (7.624)***	-0.127 (-3.275)***	0.152 (1.751)*	-0.004 (-0.107)	0.272	10.739***
Bubble period							
Crash period	0.951 (41.042)***	0.278 (5.163)***	0.018 (1.285)	0.124 (2.233)**	0.081 (5.833)***	0.436	14.249***
Post-crash Period	0.739 (50.536)***	0.628 (10.470)***	-0.089 (-1.898)*	0.511 (7.268)***	-0.096 (-1.409)	0.326	0.009

This table presents estimates of equation (3). All sub-periods in panel B and C start from 1st April and end 31st March of the given year, except the last sub-period which ends 30th September 2016. Panel D shows further analysis of 2008-2016 period, classifying into periods of market bubble (February, 2009 to February, 2011), market crash (March, 2011 to July, 2012) and post-crash (August, 2012 to September, 2016). The numbers in parentheses are *t*-statistics based on the Newey and West (1987) test for Heteroskedasticity and autocorrelation consistent standard errors. The *F* statistic tests the null hypothesis

Table 4: Herding estimations conditional on market performance based on the OLS (*continued*)

α	Up-market days		Down-market days		Adj.R ²	F statistic
	γ_1	γ_2	γ_3	γ_4		

that $\gamma_2 = \gamma_4$. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

Table 5: Herding estimations conditional on market performance based on the QR(

Quantile	θ_τ	Up-market days		Down-market days		F Statistic	Adj. R ²
		γ_1	γ_2	γ_3	γ_4		

Panel A: Total sample period;

0.05	0.539 (57.082)***	0.533 (12.087)***	-0.073 (-2.457)**	0.369 (11.124)***	-0.035 (-1.899)*	1.654	0.207
0.25	0.670 (104.470)***	0.553 (17.707)***	-0.045 (-2.384)**	0.371 (19.014)***	-0.011 (-1.324)	2.998*	0.231
0.50	0.778 (102.914)***	0.595 (20.125)***	-0.033 (-2.332)**	0.424 (17.779)***	-0.019 (-1.908)**	0.809	0.253
0.75	0.906 (78.386)***	0.698 (17.114)***	-0.038 (-2.593)***	0.573 (14.053)***	-0.037 (-3.216)***	0.006	0.279
0.95	1.109 (55.026)***	1.137 (9.100)***	-0.085 (-1.640)	1.250 (9.823)***	-0.148 (-2.515)**	0.705	0.375

Panel B: 8-year sub-periods;

(i) 2000-2008 sub-period

0.05	0.507 (29.766)***	0.639 (10.928)***	-0.102 (-3.172)***	0.500 (10.322)***	-0.059 (-2.405)**	1.547	0.249
0.25	0.683 (57.424)***	0.617 (12.903)***	-0.057 (-2.139)**	0.436 (15.162)***	-0.029 (-2.904)***	1.155	0.256
0.50	0.808 (68.483)***	0.636 (18.349)***	-0.031 (-2.112)**	0.502 (11.843)***	-0.033 (-2.844)***	0.014	0.281
0.75	0.932 (52.512)***	0.792 (15.127)***	-0.048 (-2.438)**	0.678 (10.423)***	-0.057 (-3.570)***	0.134	0.315
0.95	1.147 (49.013)***	1.179 (10.729)***	-0.090 (-2.051)**	1.481 (12.855)***	-0.184 (-5.100)***	2.803*	0.406

(ii) 2008-2016 sub-period

0.05	0.546 (56.901)***	0.524 (9.111)***	-0.116 (-3.239)***	0.355 (9.485)***	-0.053 (-2.328)**	2.909*	0.182
0.25	0.669 (84.037)***	0.467 (10.446)***	-0.030 (-0.781)	0.301 (6.716)***	-0.013 (-0.404)	0.164	0.196
0.50	0.767 (74.486)***	0.510 (13.704)***	-0.036 (-1.637)	0.323 (6.112)***	0.010 (0.249)	1.269	0.207
0.75	0.910 (68.756)***	0.554 (13.261)***	-0.046 (-2.385)**	0.313 (5.419)***	0.034 (0.937)	5.023**	0.215
0.95	1.146 (37.022)***	0.599 (6.459)***	-0.057 (-1.829)*	0.543 (4.542)***	-0.034 (-0.510)	0.112	0.244

Panel C: 4-year sub-periods;

(i) 2008-2012 sub-period

0.05	0.596 (32.490)***	0.434 (5.512)***	-0.090 (-1.836)*	0.235 (3.440)***	-0.015 (-0.449)	1.968	0.160
0.25	0.718 (53.272)***	0.365 (5.842)***	-0.003 (-0.058)	0.168 (3.132)***	0.033 (0.937)	0.519	0.187
0.50	0.840	0.394	-0.014	0.112	0.068	5.445**	0.197

Table 5: Herding estimations conditional on market performance based on the QR(continued)

Quantile	θ_τ	Up-market days		Down-market days		F Statistic	Adj. R^2
		γ_1	γ_2	γ_3	γ_4		
0.75	(54.358)***	(8.949)***	(-0.681)	(2.111)**	(2.053)**	4.983**	0.214
	0.980	0.428	-0.012	0.165	0.066		
0.95	(62.481)***	(9.026)***	(-0.654)	(2.582)***	(1.963)**	0.421	0.277
	1.195	0.602	-0.060	0.390	0.000		
	(29.265)***	(4.751)***	(-1.572)	(2.160)**	(-0.003)		
(ii) 2012-2016 sub-period							
0.05	0.526	0.555	-0.064	0.431	-0.091	0.088	0.192
	(33.730)***	(5.981)***	(-0.896)	(4.659)***	(-1.075)		
0.25	0.646	0.492	0.015	0.335	0.053	0.169	0.191
	(66.231)***	(8.558)***	(0.268)	(4.564)***	(0.606)		
0.50	0.712	0.585	-0.025	0.480	-0.029	0.004	0.212
	(61.785)***	(11.520)***	(-0.618)	(8.021)***	(-0.487)		
0.75	0.830	0.719	-0.114	0.575	-0.080	0.128	0.216
	(50.311)***	(9.447)***	(-2.338)**	(4.820)***	(-0.851)		
0.95	1.098	0.643	-0.104	0.638	-0.058	0.047	0.201
	(29.287)***	(5.235)***	(-1.480)	(2.961)***	(-0.271)		
Panel D: Analysis of 2008-2016 period;							
(i) Bubble period							
0.05	0.620	0.414	-0.106	0.127	0.022	1.233	0.141
	(23.729)***	(3.152)***	(-0.904)	(1.136)	(0.346)		
0.25	0.713	0.487	-0.126	0.154	-0.001	3.031*	0.160
	(40.465)***	(6.533)***	(-2.185)**	(2.100)**	(-0.026)		
0.50	0.819	0.537	-0.113	0.146	-0.004	1.968	0.146
	(28.078)***	(5.947)***	(-1.717)*	(1.636)	(-0.067)		
0.75	0.969	0.540	-0.102	0.107	-0.015	0.582	0.158
	(48.257)***	(6.574)***	(-1.813)*	(1.006)	(-0.140)		
0.95	1.226	0.548	-0.144	-0.372	0.515	2.161	0.167
	(22.389)***	(2.498)***	(-0.744)	(-1.004)	(1.167)		
(ii) Crash period							
0.05	0.705	0.089	0.083	0.003	0.120	0.141	0.141
	(32.182)***	(1.125)	(2.052)**	(0.048)	(2.240)**		
0.25	0.840	0.198	0.039	0.001	0.113	0.623	0.147
	(29.893)***	(1.677)*	(0.636)	(0.009)	(1.334)		
0.50	0.945	0.261	0.031	0.074	0.089	0.472	0.188
	(35.769)***	(3.009)***	(0.627)	(0.668)	(1.116)		
0.75	1.059	0.351	0.005	0.150	0.077	0.790	0.225
	(34.913)***	(3.543)***	(0.114)	(1.189)	(0.968)		
0.95	1.207	0.439	-0.023	0.457	-0.017	0.001	0.363
	(20.336)***	(2.256)**	(-0.298)	(1.815)*	(-0.088)		
(iii) Post-crash period							
0.05	0.514	0.592	-0.086	0.456	-0.102	0.025	0.188
	(33.998)***	(5.983)***	(-0.963)	(5.068)***	(-1.250)		
0.25	0.633	0.583	-0.101	0.420	-0.090	0.013	0.182
	(58.451)***	(8.539)***	(-1.452)	(5.198)***	(-0.978)		
0.50	0.704	0.591	-0.022	0.472	-0.030	0.006	0.199
	(66.369)***	(8.846)***	(-0.303)	(5.898)***	(-0.319)		
0.75	0.810	0.752	-0.125	0.532	-0.089	0.063	0.196
	(45.864)***	(7.588)***	(-1.755)*	(3.997)***	(-0.624)		

Table 5: Herding estimations conditional on market performance based on the QR(continued)

Quantile	θ_τ	Up-market days		Down-market days		F Statistic	Adj. R^2
		γ_1	γ_2	γ_3	γ_4		
0.95	1.097 (26.349)***	0.633 (4.129)***	-0.134 (-1.318)	0.580 (2.154)**	0.038 (0.124)	0.327	0.157

This table presents estimates of equation (5) at different quantile levels for the total sample period, eight-year sub-periods, four-year sub-periods, and analyzing 2008-2016 sub-period into market bubble (February 2009 to February 2011), market crash (March 2011 to July 2012) and post-crash (August 2012 to September 2016) periods. All sub-periods in panel B and C start from 1stApril and end 31stMarch of the given year, except the last sub-period which ends 30thSeptember 2016. The results relating to the 2000-2004 and 2004-2008 sub-periods are not reported under panel C since their results are not significantly different from those reported under the 2000-2008 sub-period in panel B. The F statistic tests the null hypothesis that $\gamma_2 = \gamma_4$. The numbers in parentheses are t-statistics based on bootstrap standard errors. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels respectively.

5. Conclusion

The study focuses on examining time-varying nature of investors' herding attitudes in a frontier stock market, the CSE of Sri Lanka. In the presence of structural limitations of frontier markets, compared to developed and emerging stock exchanges, such as lower transparency of informational environment, illiquidity and relatively low number of stocks actively traded, it would be expected that investors are more likely to imitate others, discarding their beliefs, information and fundamentals in stock trading. Supporting this general prediction, both the OLS and the QR evidence find a strong tendency to herd at the aggregate market level as well as both raising and falling market days of the total sample period. However, it is interesting to note the results of the sub-period analyses which reveal changes of herding attitudes to negative herding and its tendency to shift away over different episodes of the market. The herding is strongly evident during the period of political uncertainty, resulting from the civil war. It appears to continue even after this uncertain time period, raising the market to a speculative bubble which bursts subsequently as a consequence of investors' negative herding attitudes.

The negative herding behavior may be attributed to investors' overconfidence as a result of significant gains realized in the period of market bubble, and/or increased risk-averseness of investors resulting from irrational fears due to uncertain market conditions, both of which cause trading of stocks excessive and exaggerated way, increasing the price dispersions above the rational level. Therefore, this evidence infers that herd behavior would result to a market bubble whereas negative herding would cause to burst of the bubble, leading to market crash. The evidence on herd behavior is mostly absent during the period after the market crash; therefore, investors appear to have learnt the irrationality of herding with significant losses experienced during the period of market crash. When the results are taken together, they suggest that period-specific characteristics of the market and the associated psychological effects to investors such as overconfidence and panics would cause changes to their beliefs and behaviors, the experiences of which would subsequently produce a learning effect to minimize irrational behaviors such as herding. Further, the results indicate that the absence of herding in the previous studies conducted by Sewwandi (2016) and Xiaofang and Shantha (2017)²² may be primarily due to limiting the analysis to the total sample period, which results in aggregation of herding, negative herding and anti-herding behaviors occurred at different times over their sample periods.

The major implications from the findings of this study are as follows. First, consistent with Bekiros et al. (2017), Klein (2013), Zhou and Anderson (2013) and Clements et al. (2017), the evidence suggests that herd behavior is a dynamic phenomenon, thus, varying over time depending on period-specific characteristics of the market. Second, as a novel evidence to the herding literature, the findings support the AMH, implying that investors are likely to realize the irrationality of herding and control such behaviors when they get

²²Here, concern on the OLS results, not the QR results of the study conducted by Xiaofang and Shantha (2017).

experience in stock trading over time. Third, since the evidence highlights that, apart from the structural limitations of a frontier market, external environmental events would affect investors' psychological state, causing irrational behaviors in trading financial assets, educational initiatives such as workshops and training programs should be undertaken continuously, in addition to implementing policy reforms to improve market's stability and efficiency status. Such educational initiatives would facilitate the investors to obtain sufficient knowledge, which, along with their trading experiences, would improve their sophistication, thereby, reduce irrationality in making investment decisions. Fourth, it should also be noted that this study attempts to detect a particular form of irrationality of investors in trading financial assets. Investors would exhibit other types of irrational behaviors in their investment decision making process. Further research covering other types of behavioral biases will provide greater insights into the nature of investors' behavior, based on which educational initiatives could be effectively planned in order to minimize their irrational behaviors.

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